Accurate Determination of GPS Receiver with Different Classification Methods

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Abstract: One of the instruments for determination of position used in several applications is the Global Positioning System (GPS). With a cheap GPS receiver, we can easily find the approximate position of an object. Accuracy estimation depends on some parameters such as dilution of precision, atmospheric error, receiver noise, and multipath. In this study, position accuracy with GPS receiver is classified in three classes. Nine classification methods are utilized and compared. Finally, a new method is selected for classification. Results are verified with experimental data. Success rate for classificationis approximately 84%.

Keywords: GPS, DOP, classification, error.

1 Introduction

Nowadays localization has become an important necessity in life. One of the best methods for estimation of position is Global Positioning System (GPS). GPS receivers can estimate position, velocity and time. GPS position errors are determined by pseudo-range errors and satellite geometry. The main pseudo-range measurements errors can be divided into three groups: ephemeris errors and satellite clock errors, atmospheric errors, and user receiver errors (frequency drift, pseudo-noise sequence phase drift, and signal detection time). Ephemeris errors and satellite clock errors occur when the GPS message does not transmit the correct satellite location. With the use of measurements of pseudo-ranges on two frequencies, the ionospheric amendment (correction) of measurements of pseudo-range on a C/A code for ground receivers is determined. After obtaining the pseudo-range and Doppler frequency measurements errors connected to stability of a frequency generator, the stability of pseudo-noise sequence phase drift and stability signal detection time, are called by various synchronization of user's receiver time and GPS-system. The dynamics of an oscillator of receiver frequency generator and pseudo-noise sequence phase drift and accuracy of signal detection time is investigated [1].

Several researches have been conducted on enhanced accuracy of receivers. Some research works have been carried out on the use of extra sensors for integration with GPS receiver such as inertial sensor [2-4]. Another research work was carried out on differential methods such as Differential GPS (DGPS) and Wide Area Augmentation System (WAAS) for increase accuracy [5,6]. Some other researchers used software methods such as Neural Networks (NNs) and fuzzy for improving accuracy [7-9].

These methods need to change hardware or software. It is useful to know the accuracy of some applications. The aim of this study is on classified accuracy of GPS receivers with classification methods. Some of the methods used for classification have some disadvantages[10,11].These methods have high error in classification. In this study, we implemented nine methods thatproposed method has a low classification error.

The remainder of this paper is organized as follows. Section 2 describes extracted data for implementation of algorithms. Section 3 describes the structure of an algorithm used in this study. Section 4 introduces three classes of localization accuracy. Section 5 discusses feature vectors. Section 6 prepares data for classification. Section 7 discusses nine methods of classification. The final section verifies algorithms and compares methods and gives concluding remarks.

2 Data Set

Data were recorded with a GPS receiver for duration of 18 hours. These data were captured in National Marine Electronics Association (NMEA) format. Rate of output was 1 Hz. These data were classified based on

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extract position and other data. Fig.1shows the setup of the test. It was used as a GPS development unit for NAVMAN which could send data based on two binary protocols and NMEA. A block diagram of this setup is shown in Fig.2. In this study, NMEA protocol was utilized. NMEA has some sentences such as $GPGGA, $GPGSV, and $GPRMC. $GPGGA and $GPGSV are normally used for analyzing data.

Scattering of data is shown in Fig.3. It can be seen from Fig.3 that the accuracy of position changes at different times. With additional time, accuracy is better at 20 meters.

3 Structure of Algorithm

Fig.4 shows the classification steps. Step one is outputs data extraction of GPS receiver, where captured and proper data were extracted. Step two is preprocessing of data that were removed from improper data. Step three is the selection of proper features. The final step is the classification of data into three classes.

4 Classes of Localization Accuracy

In this study, we have defined three classes of localization accuracy which include accurate, moderate and inaccurate. Accuracy values of these classes are shown in Table 1.

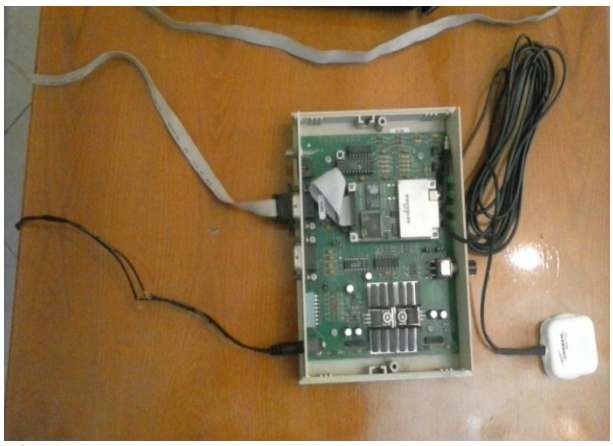

Fig. 1 Test setup.

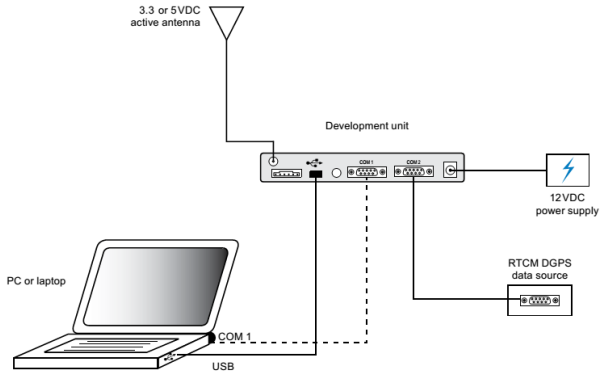

Fig. 2 Development unit and test equipments setup.

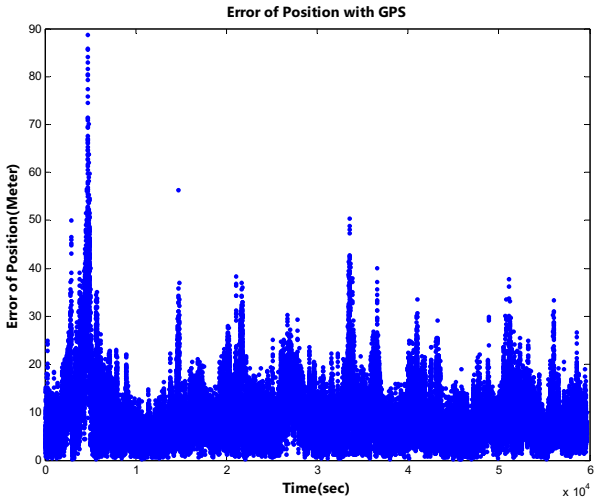

Fig.3 Positioning error of the GPS receiver.

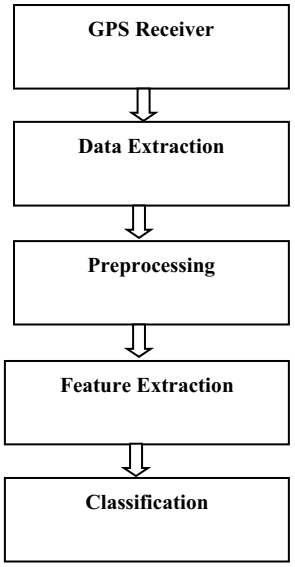

Fig.4 Flow chart of implementedalgorithm.

5 Feature Vector

GPS receivers provide some information that is sent in output. These parameters are used by few applications. Important parameters are Carrier to Noise Ratio (CNR), number of satellites in view, elevation and azimuth of satellites in view, Geometric Dilution of Precision (GDOP), position, velocity and time. In this study, these parameters are shown in Table 2. They are used for classification.

Table 1 Class of localization accuracy in meters**.**

Accuracy	Accurate	Moderate	Non-accurate
Error range	0-10	10-20	>20

Table 2 Feature selection for classification.

Feature	Sat view	CNR	μ_{CNR}	σ_{CNR}

Sat view is the number of satellites in view, CNR is carrier to noise ratio, $\mu_{CNR}$is the average of a carrier to noise ratio of all satellites in view, and σ_{CNR} is the variance of carrier to noise ratio of all satellites.

To evaluate these parameters, we use the Fisher's discriminant ratiowhich is shown in Eq.(1) [12]:

$$FDR=\sum_{i=1}^{3}\sum_{j\neq i}^{3}\frac{(\mu_i-\mu_j)^2}{\sigma_i^2+\sigma_j^2} \quad (1)$$

where μ_i, σ_i^2 and μ_j,σ_j^2 represent means and variances for classes i and j, respectively, and they are summed over all the classes 3.

If this ratio is calculated for all features, the strength of each parameter can be evaluated. Results are shown in Fig.5.

It was determined that GDOP has the longest effect while Sat view has the lowest effect, but because of the number of features are low, there is no need to decrease the features such as Sat view.

6Preprocessing and Verification

For correct classification, there is need to prepared data and removed false data. In this section, two steps were used for preparing of data while one step was used for verification.

6.1 Outlier Removal

An outlier is defined as a point that lies very far from the mean of the corresponding random variable. This distance is measured with respect to a given threshold, usually a number of times the standard deviation. For a normally distributed random variable a distance of two times the standard deviation covers 95% of the points, and a distance of three times the standard deviation covers 99% of the points. Points with values very different from the mean value produce large errors during training and may have disastrous effects. These effects are even worse when the outliers are the result of noisy measurements.

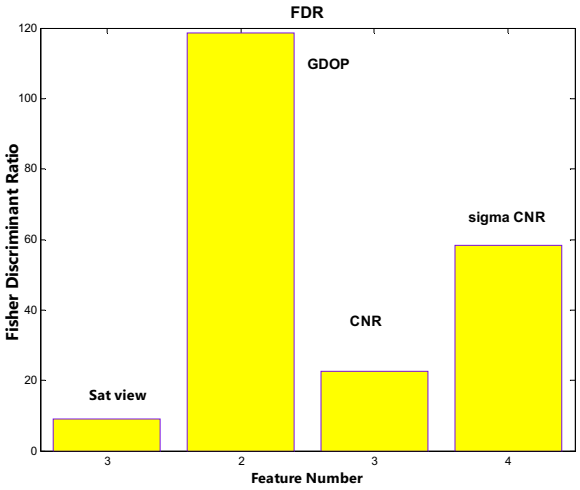

Fig. 5 Fisher ratio for feature vector.

Table 3 Dynamic range of features.

Feature	Minimum value	Maximum value	Unit
Sat view	4	12	Number
GDOP	0.9	4.1	-
CNR	41.5357	49.2612	dB-Hz
σ_{CNR}	0.2674	74.8126	dB-Hz

To have correct data for analysis and validation of data, there is need to removed data that are not valid. In this study, we removed data that have CNR larger than 55 dB-Hz or less than 30 dB-Hz and also data that haveGDOP more than 50. With the removal of these data, data were selected that were valid and suitable for test and validation.

6.2DataNormalization

First step for starting classification is normalization. These data belong to each feature and they are in different range. To have equivalent influence features in classification, there is need to normalize captured data. Table 3 shows the dynamic range of features.

For normalization, we used Min-Max method as shown in Eq. (2):

$$x_{new}=\frac{x_i-\min(x)}{\max(x)-\min(x)} \quad (2)$$

where x=(x_1 ,...,x_n) and x_{new} is i-th normalized data.In this step, all data were normalized in the range of 0 to 1.

6.3 Verification

K-fold partition of the data set was created. For each K experiments, K-1 folds are used for training and the remaining one for testing. Then, the average error across all K trials is computed as follows:

$$\bar{E}=\frac{1}{k}\sum_{i=1}^{k}E_i \quad (3)$$

where E_1, ..., E_k are the errors obtained in k runs.The advantage of this method is that it doesn't matter how the data is divided. Every data point needs to be in a test set exactly once, and needs to be in a training set K-1times. The variance of the resulting estimate is reduced as K is increased. In this study, K is assumed as 10.

7Classifications

There are some classifiers that can be used for classification. In this study, nine classifiers were investigated and the results were shown [12,13].

7.1 Euclidean Minimum Distance

This method is the simplest approach for classification. First, we calculate a mean of feature vector for each class and therefore calculated the distance between each test vector with these mean vectors. If a mean vector of class i has minimum distance to test vector j, class test vector j is i. The relation for this classifier is given as follows:

$$\|(x - m_i)\| = \sqrt{(x - m_i)^T (x - m_i)} < \|(x - m_j)\| \ \forall i \neq j \quad (4)$$

In Eq. (4), m_i is the mean vector in class i and x is a test vector. In this study, number of classes is three and dimension for each test vector is 4×1. By using this method and assuming that k is equal to 10, we will have an error of classification equal to 46.2791%. Table 4 shows the confusion matrix for this method.

It can be seen that this method cannot classify more than 50% of total samples correctly. This method is a linear classifier and the overlap between the three accuracy classes in the features makes it impossible for any linear classifier to assign a GPS measurement to a unique accuracy class based on these features.

A receiver operating characteristic or ROC curve is shown in Fig.6.

7.2 Mahalanobis Minimum Distance

In this method, mean and variance of feature vector in each class is calculated. Then, Mahalanobis distance for each test vector with mean feature vector is computed. Each class that has minimum distance to test vector is a class of this test vector. The relation is as follows:

$$\sqrt{(x - m_i)^T S^{-1} (x - m_i)} < \sqrt{(x - m_j)^T S^{-1} (x - m_j)} \ \forall i \neq j \quad (5)$$

where m_i is a mean vector in class i and S is variance matrix belonging to featured vector and x is a test vector. By using this method and assuming k equal 10, then mean error is 47.4419% and confusion matrix is shown in Table 5.

Table 4 Confusion matrix for Euclidean minimum distance.

		Actual class		
		1	2	3
Estimated class	1	8.3721	6.9767	4.1860
	2	10.2326	22.3256	16.2791
	3	1.8605	6.7442	23.0233

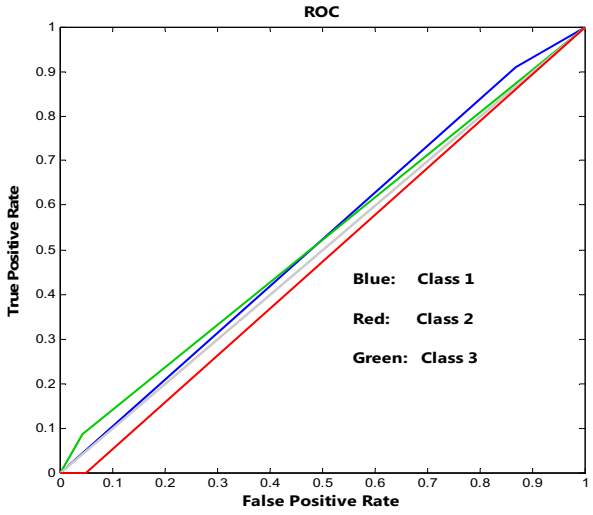

Fig.6 ROC curve for Euclidean minimum distance classifier.

Table 5 Confusion matrix for Mahalanobis minimum distance classifier.

		Actual class		
		1	2	3
Estimated class	1	16.9767	10.0000	1.8605
	2	26.2791	30.0000	3.9535
	3	0	5.3488	5.5814

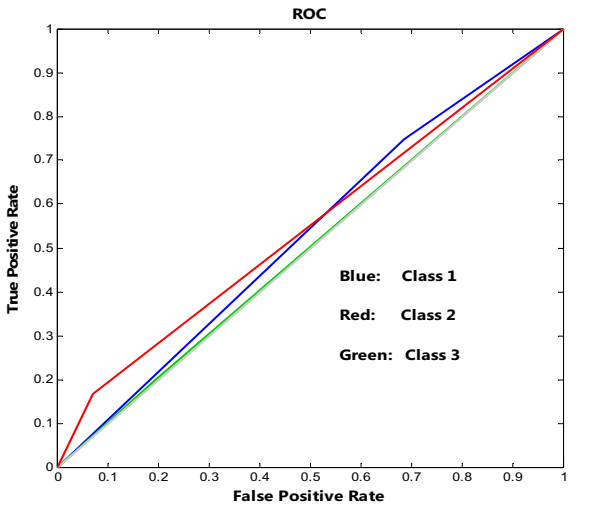

Fig.7ROC curve for Mahalanobis minimum distance classifier.

ROC curve is shown in Fig.7. It can be seen that this method cannot classify more than 52% of total samples correctly, because this method is a linear classifier.

7.3 Bayesian & Likelihood

This method is based on Bayesian decision theory. In Bayesian method, we must know the Probability Density Function (PDF), P(X|Wi).Therefore, this function must be calculated. In this method, Gaussian distribution for PDF is assumed. With maximum likelihood method, we can calculate mean vector and variance matrix as follows:

$$m_{\mathrm{ML}} = \frac{1}{N}\sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{X_i} \quad (6)$$

$$S_{ML} = \frac{1}{N}\sum_{i=1}^{N}(X_i - m_{ML})\,(X_i - m_{ML})^T \quad (7)$$

Now we can calculate PDF as follows:

$$P(X_i|\omega_i) = \exp\left(-\frac{1}{(2\pi)^{l/2}|S_{ML}|^{l/2}}(X_i - m_{ML})^T S^{-1}(X_i - m_{ML})\right) \quad (8)$$

$$P(\omega_j|X) = \frac{P(X|\omega_j)P(\omega_j)}{P(X)} \quad (9)$$

where N is number of samples in class j. To classify the accuracy of position, we know that the probability of class one is more than that of other classes, so we assume that $P(w_1)$=60%, $P(w_2)$=25%, and $P(w_3)$=15%. Results show that classification error is 52.0930%. Confusion matrix for this method is given in Table 6.ROC curve is shown in Fig.8.

7.4 K-Nearest Neighbor

KNN classifier is a simple non-parametric method for classification. Despite the simplicity of the algorithm, it performs very well, and is an important benchmark method. KNN classifier requires a metric d and a positive integer K. KNN rule holds the position of training samples and their class. When decision about new incoming data is needed, distance between query data and training samples is being calculated. Based on the defined threshold for the rule (it is the K number), K samples with least distances are selected and the class with more samples inbound is the result. In other words, for example if there are 2 or 3 features for a classification situation, the position of training samples and input sample can be visualized on 2D and 3D Cartesian coordinates. The process of finding the result is like drawing a circle (sphere) centered on input location and increase radius until K samples are embedded inside the circle (sphere) and then a class with more samples inbound is the result. Fig. 9 shows this method. For K=3, inside the small circle there are two triangles and one square, the result is triangle class.

KNN is a classifier with 100% accuracy on training data set, because the position of training samples and their class are constant during the classification process.

Table 6 Confusion matrix for Bayesian and likelihood.

		Actual Class		
		1	2	3
Estimated class	1	10.0000	1.1628	1.8605
	2	10.4651	18.1395	13.2558
	3	9.5349	15.8140	19.7674

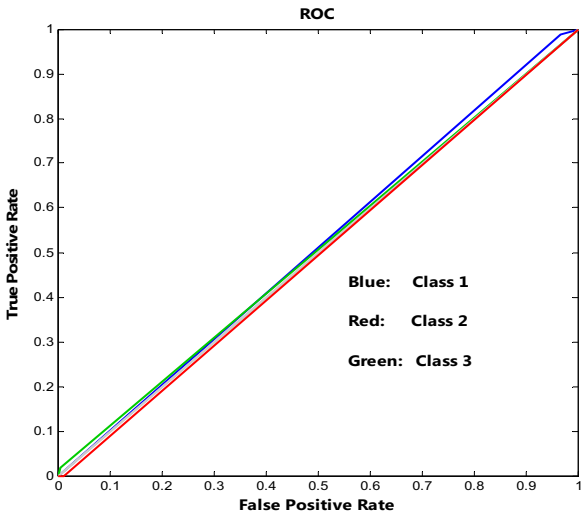

Fig.8 ROC curve for Bayesian and likelihood classifier.

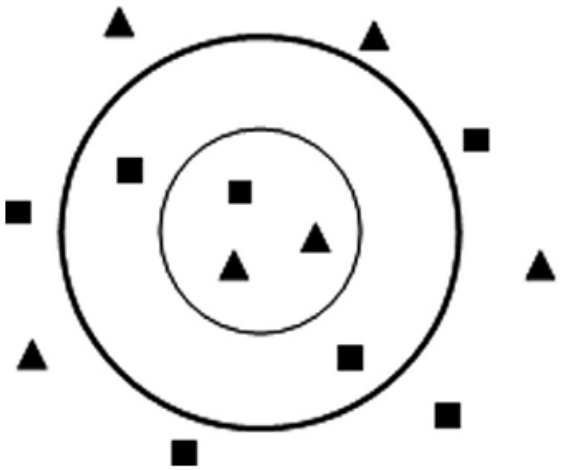

Fig.9 KNN algorithm for a situation with two classand two features.

In this work, variable K value is used between 1 and 10. First step, neighbors are assumed to be 3, and thenerror of this method for classification will be 16.7442% and the confusion matrix is given in Table 7.ROC curve is shown in Fig.10.

Second step, neighbors are assumed to be 10, and then error of classification is given as 30.9302%. Confusion matrix for this method is given in Table 8.It can be seen that KNN classifier with 3 neighbors has less error than classifier with 10 neighbors.

Table 7 Confusion matrix for KNN with 3 neighbors.

		Actual class		
		1	2	3
Estimated class	1	9.7674	7.9070	0
	2	3.2558	55.3488	3.9535
	3	0.2326	1.3953	8.1395

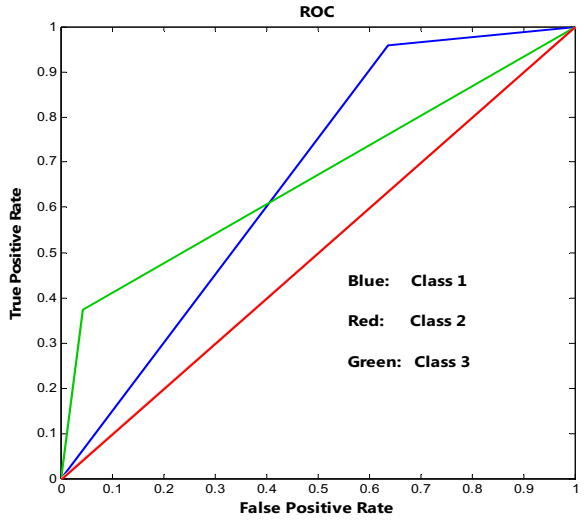

Fig.10 ROC curve for KNN with 3 neighbors classifier.

Table 8 Confusion matrix for KNN with 10 neighbors.

		Actual class		
		1	2	3
Estimated class	1	14.6512	7.4419	3.0233
	2	10.4651	40.0000	7.2093
	3	0.4651	2.3256	14.4186

7.5 Least Square

The attractiveness of linear classifiers lies in their simplicity. Thus, in many cases, although we know that the classes are not linearly separable, we still wish to adopt a linear classifier, despite the fact that this will lead to suboptimal performance from the classification error probability point of view. The goal now is to compute the corresponding weight vector under a suitable optimality criterion. In this method, we define a discriminant function for each class and each test vector that has maximum value in discriminant function in class i, so that the class of test vector is i. Discriminant function is defined as follows:

$$g_j(X) = \omega_j^T X + \omega_{jo} \quad j=1,2,3 \tag{10}$$

$$g_i(X) > g_j(X) \quad \forall\, i \neq j \tag{11}$$

where ω_j and ω_{j0} are unknown parameters. The least square method is used for calculating ω_j and ω_{j0}. Error of classification is 52.3256% and confusion matrix is given in Table 9.ROC curve is shown in Fig.11.

Furthermore, least square method has a low error, but this method cannot classify test vector of class 3.Therefore, it is not a proper method for classification.

Table 9 Confusion matrix for least square method.

		Actual class		
		1	2	3
Estimated class	1	0.6977	20.0000	4.4186
	2	6.5116	32.5581	18.6047
	3	0.9302	1.8605	14.4186

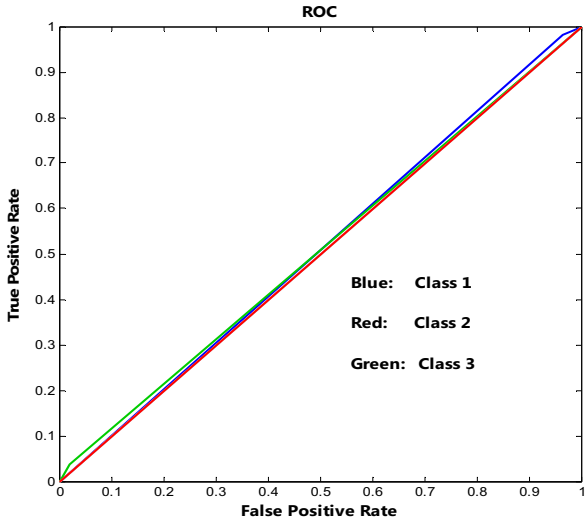

Fig.11 ROC curve for least square classifier.

Table 10 Confusion matrix for PCA.

		Actual class		
		1	2	3
Estimated class	1	3.9535	0.9302	8.8372
	2	28.8372	9.5349	12.0930
	3	20.2326	0.9302	14.6512

7.6 PCA

The basic approach in principal components or Karhunen-Lo´eve transforms is conceptually quite simple [11]. First, the d-dimensional mean vector μ and d×d covariance matrix Σ are computed for the full data set. Next, the eigenvectors and eigenvalues are computed. Eigenvectors are columns of Aj matrix. We calculate $\|A_j X\|$ for each test vector and for all class. Each test vector with maximum value for class j, is grouped in class j. The relation is as follows:

$$\|A_j X\| > \|A_i X\| \quad \forall\, i \neq j \tag{12}$$

Error of classification is 71.8605%and confusion matrix is given in Table 10.This classifier cannot be

suitable for this work, because it cannot classify data belonging to class 1 and 3.

7.7 Neural Network

NNs have emerged as an important tool for classification. The recent vast research activities in neural classification have shown that NNs are a promising alternative to various conventional classification methods.

NNs are one method for decomposing a complex system into simpler parts so as to realize it. A set of nodes and connections between nodes are components of NNs. The nodes are known as computational units of NNs and the connections determine the information flow between nodes. Artificial Neuron Networks (ANNs) are one of networks that see the nodes as artificial neurons. An artificial neuron is a computational model inspired in the natural neurons.

In artificial neurons, inputs are multiplied by weights and then calculated by an activation function. Another function estimates the output of the artificial neurons. ANNs combine artificial neurons [14]. ANNs are non-linear mapping structure. ANNs can recognize correlated patterns between input data set and corresponding target values. ANNs has huge capacity in prediction, pattern recognition, data compression, decision-making, and etc. ANNs are recently used in the classification problem where regression model and other statistical techniques have traditionally been applied [15,16]. Now, there are many different models of ANNs. The differences might be the topology, the functions, the hybrid models, the accepted values, the learning algorithms, and etc. However, back-propagation algorithm is one of the most common models of ANNs. In back-propagation algorithm, the network gains inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. There may be several hidden layers. By this work, a difference between actual and expected results is estimated (error). Finally, the back-propagation algorithm is to decrease this error, until the ANN learns the training data set [17].

In this study, the feed forward back-propagation NN is used, which consists of input layer, hidden layer and output layer. Number of inputs is the same as the size of feature vector (equal to 4). Number of outputs is the same as the number of classes (equal to 3). Number of neuron in second layer is equal to 30. The architecture of applied NN is shown in Fig.12.After learning this NN, error of this method is 30.6657% and confusion matrix is given in Table 11.ROC curveis shown in Fig.13.

It can be seen that this method can classify more than 70% of total samples correctly. This method is a non-linear classifier and proper for classification in this work.

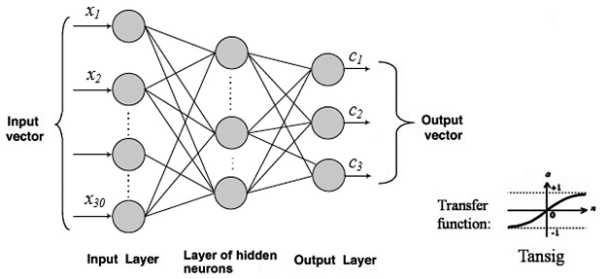

Fig.12 The architecture of applied NN.

Table 11 Confusion matrix for NN.

		Actual class		
		1	2	3
Estimated class	1	66.1362	2.0245	0.0398
	2	23.8439	3.1721	0.0689
	3	3.2272	1.4614	0.0260

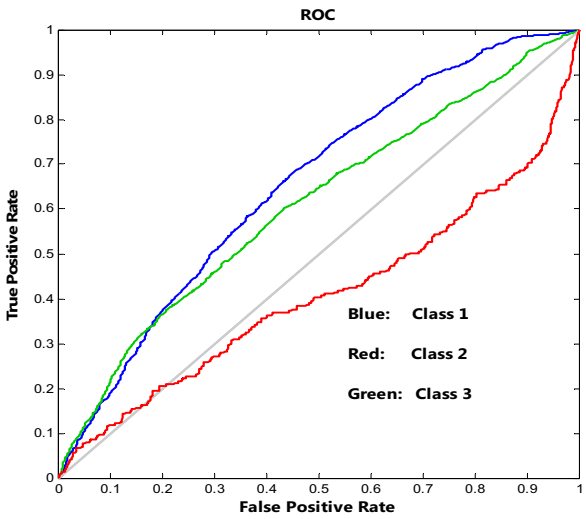

Fig.13 ROCcurve for NN classifier.

7.8 Hierarchical Classier using Class Unfolding

A hierarchical classification strategy is developed to address the class ambiguity problem via the class unfolding approach (HCCU). HCCU strategy is proven to be superior with respect to other hierarchical configuration [10]. Fig. 14 shows a particular HCCU for the classes presented in this paper.

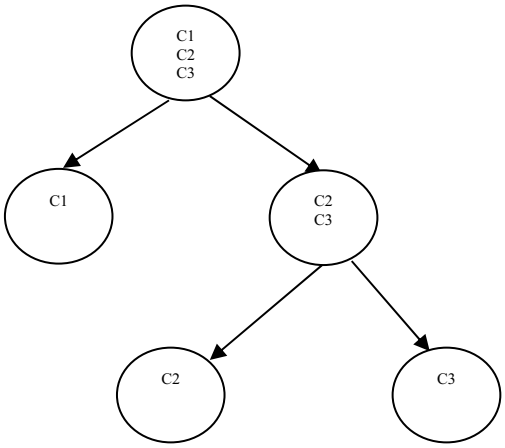

Fig.14 Structure of the HCCU for the three classes.

Error of classification is 17.2093% and confusion matrix is given in Table 12. ROC curve is shown in Fig.15. It can be seen that this method can classify more than 82% of total samples correctly.

Table 12 Confusion matrix for HCCU.

		Actual class		
		1	2	3
Estimated class	1	21.3953	10.9302	1.1628
	2	3.7209	55.1163	2.0930
	3	0	0.2326	5.3488

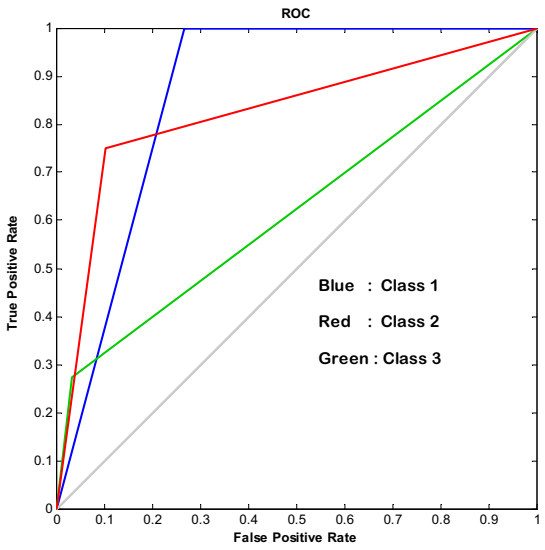

Fig.15 ROC curve for HCCU classifier.

7.9 Hierarchical Classier using Class Unfolding of Modified

In this paper, we propose a hierarchical classification via the class unfolding approach that modified(HCCUM) for classification. We know that class 2 has a confliction with class 1 and class 3. HCCUM had solved this problem. Fig. 16 shows new method(HCCUM) that proposed for the classes presented in this paper.

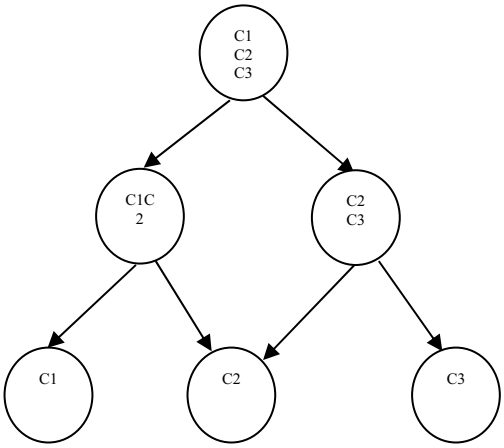

Fig.16 Structure of the HCCUM for the three classes.

Error of classification is 16.3050% and confusion matrix is given in Table 13. ROC curve is shown in Fig.17. It can be seen that this new approach can classify more than 83% of total samples correctly.

Table 13 Confusion matrix for HCCUM.

		Actual class		
		1	2	3
Estimated class	1	21.8605	11.1628	0.4651
	2	3.2558	56.2791	1.3953
	3	0	.2326	5.3488

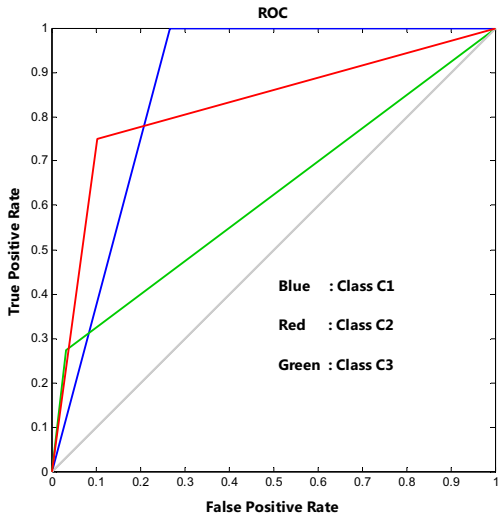

Fig.17 ROC curve for HCCUM classifier.

8Comparison and Verification

In this section, the results of nine classifiers are compared. Table 14 shows a comparison of the error of these methods.

It can be seen that classifiers such as HCCUM and KNN can be used for classification in this work. Also, it can be understood that best approach for the classification of position accuracy is HCCUM, while PCA and Mahalanobis methods have the most error.

Table 14 Comparison ofnine classifiers.

Classifier	Classification error (%)
PCA	71.8605
Least square	52.3256
Bayesian and likelihood	52.0930
Mahalanobis minimum distance	47.4419
Euclidean minimum distance	46.2791
KNN (with K=10)	30.9302
NN	30.6657
HCCU	17.2093
KNN (with K=3)	16.7442
HCCUM	16.3050

9Conclusion

This paper has dealt with GPS localization accuracy classification. For classification of position accuracy, nine classifiers were investigated and a newapproach that proposed in this paperwas selected for this work. Experimental data were recorded with a GPS receiver and preprocessing for removal of improper data and was normalized. These methodswere implemented and verified. This paper presents experimental results to validate the effectiveness of the accuracy classification algorithms.The overlap between the three accuracy classes in the features makes it impossible for any linear classifier to classify correctly.Results obtained show that HCCUM classifier had the least error. New approach (HCCUM) was the best solution for classification.This classifier had a successful rate of about 84%.

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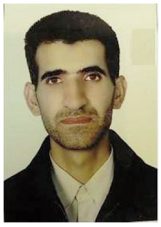

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